DTU Library

Toolbox for uncertainty; Introduction of adaptive heuristics as strategies for project decision making

Stingl, Verena; Geraldi, Joana

Published in:
Conference proceedings of International Research Network on Organizing by Projects (IRNOP 2017)

Publication date:
2017

Document Version
Peer reviewed version

Toolbox for uncertainty: Introduction of adaptive heuristics as strategies for project decision-making

Verena Stingl, *PhD fellow, Technical University of Denmark, Department of Management Engineering, verst@dtu.dk*

Joana Geraldi, *Associate Professor, Technical University of Denmark, Department of Management Engineering, joasta@dtu.dk*

Toolbox for uncertainty: Introduction of adaptive heuristics as strategies for project decision-making

Keywords: Adaptive heuristics, decision-making, uncertainty, ecological rationality, project decisions

Abstract:

This article presents adaptive heuristics as an alternative approach to navigate uncertainty in project decision-making. Adaptive heuristic are a class of simple decision strategies that have received only scant attention in project studies. Yet, they can strive in contexts of high uncertainty and limited information, which are the typical project decision context.

This article develops a conceptual model that supports a systematic connection between adaptive heuristics and project decisions. Individual adaptive heuristics succeed only in specific decision environments, in which they are 'ecologically rational'. The model builds on the individual definitions of ecological rationality and organizes them according to two types of uncertainty ('knowable' and 'unknowable'). Decision problems and heuristics are furthermore grouped by decision task (choice and judgement). The article discusses several resulting propositions for future research and analyses the scant project literature on heuristics with regard to its fit to the model and the propositions.

This conceptual approach supports future prescriptive research that can foster the development of efficient and intuitively applicable decision support tools. It finally highlights current boundaries of research on adaptive heuristics regarding the missing reflection of different types of uncertainty.

1. Introduction

Projects take place in ambiguous and evolving environments. These environments require continuous, repeated and fast paced decisions. Yet, the information to ground these decisions in is often limited, intertwined and ambiguous, historical data is scarce, and personal relationships are complex. In short: project decisions are taken in an environment of particularly high uncertainty.

Many rational and normative approaches have been put forward to navigate this uncertainty, and to support project decision-making (Rolstadås et al., 2014). However, these approaches are typically information and time demanding, sometimes difficult to apply, and in consequence not always well accepted in practice (Hartono and Yap, 2011) . Indeed, practitioners often stress the importance of expertise and intuition (Leybourne and Sadler-Smith, 2006). While the success of either 'rational' and intuitive decision strategies is debated, reliable decision strategies that come more naturally to the pre-existing professional practice are likely to receive higher adoption.

In this paper, we will introduce such an alternative approach for project decision support. We will build on the concept of 'adaptive heuristics' (e.g. Gigerenzer et al., 2011; Gigerenzer and Gaissmaier, 2011). Adaptive heuristics are simple decision strategies that, similar to intuitive reasoning, build on experience, limited information, and are useful in situations of high uncertainty. Yet, they have demonstrated to be robust and reliable decision strategies in complex, ambiguous and uncertain managerial decision contexts, such as evaluating business opportunities, identifying active customers, or real-estate choices (Artinger et al., 2015). Overall, research suggests that adaptive heuristics permit constructing decision strategies that are both efficient (fast) and effective (frugal), and are more in line with 'natural' cognitive processes of expert reasoning (Gigerenzer and Brighton, 2009). Finally, adaptive heuristics facilitate eliciting and sharing expert knowledge (Rieskamp and Otto, 2011), hence allow the discussion, formalization, testing and teaching of expert judgement. In this regard, adaptive heuristics act as an vehicle to turn tacit into explicit knowledge (Bingham and Eisenhardt, 2011), and contribute not only to constructing fast and frugal decision strategies, but also to learning in project organizing.

In summary, project decisions usually take place in an environment in which adaptive heuristics can strive, while more information demanding approaches struggle: high uncertainty, high time pressure, limited historical data, and reliance on expert intuition. They are adopted intuitively and can be used as mechanisms for learning and reflection in practice.

Yet, project studies have only very recently started to explore heuristics as decision strategies (Albar and Jetter, 2011; Eriksson and Kadefors, 2017; Hartono and Yap, 2011; Mathews, 2010).

The aim of this paper is to introduce adaptive heuristics to the project domain, and argue how project studies and practice can profit from their application. Our argument will build on a "Borrowing and Extending" approach (Zahra and Newey, 2009). We will theorize at the interface of adaptive heuristics and project studies to spark research in a new context that can inform back to research on adaptive heuristics.

As the name suggests, adaptive heuristics are only suitable in a specific decision environment, an environment in which they are 'ecologically rational'. Therefore, this article asks: What kind of adaptive heuristics can support different project decisions, and why?

To link existing research in other domains with potential applications in projects, we will propose a new conceptual model of heuristics and decisions. The proposed model reflects the decision context through the dimensions uncertainty type and decision task. This provides a systematic connection between adaptive heuristics and project decisions, providing a starting point for future prescriptive research.

With this paper, we contribute to project studies, project practitioners and the growing research community studying adaptive heuristics. In the domain of project studies, we provide an alternative theory for prescriptive research on decisions, and a new theoretical lens to analyse observed decision-making behaviour. Regarding project practice, adaptive heuristics can foster the development of new effective and intuitively applicable decision support tools. Finally, we purport to contribute beyond project studies to the adaptive heuristics research community by providing a new way of organizing adaptive heuristics based on the decision environment in which they strive.

The paper has five parts. First, we will provide an overview of the literature on project decisions, and establish the research gap on application of adaptive heuristics. Second, follows the presentation of adaptive heuristics and their key theoretical concepts. Third, we will introduce a simple conceptual model that allows common classification of decision types and adaptive heuristics. Fourth, we present three key propositions building on the model, and reflect the scant literature on adaptive heuristics in projects through the lens of the model. Fifth, we will provide a discussion of the model and its limitations, and conclude with an outlook on future research.

2. Literature review: project decisions

Decision-making is a core task in projects, consequently the literature on project decision is abundant, covering a broad range of decision types and theoretical angles. Broadly, the literature can be grouped in two areas: the normative, and the descriptive (Rolstadås et al., 2014). In their review of behavioural decision-making, Stingl and Geraldi (2017) identified 386 publications in key project journals addressing decisions, of which only 88 were descriptive, discussing behavioural decision-making. Hence, the main body of project decision research is concerned with normative decision theory and, foremost, decision support tools to accommodate normative views on rational decision-making.

Decision support tools in the literature have matured in complexity and sophistication. Different probabilistic approaches for project decision-making, building on expected value models, have been proposed since the mid of the past century. Historical examples are Pound's Pairwise-Comparison for selection of research projects (1964), the Analytical Hierarchy Process (AHP) proposed by Saaty in the 1980ies (for a review in projects see Al-Subhi Al-Harbi, 2001), decision trees for solving multiple constrained resource scheduling problems (Patterson, 1984), or the Program Evaluation and Review Technic (PERT) for a stochastic approach to project scheduling (Miller, 1962). Rolstadås et al. (2014) provide a comprehensive overview of classical and advanced deterministic and stochastic methods in their book "Decision Making in Projects"

Starting in the 1990ies, classical probabilistic decision theory was supplemented by fuzzy theory as an alternative to the classical decision support methods (e.g. Zeng et al. 2007), or to supplement established methods like AHP (e.g. Huang et al., 2008). Finally, increasing computing capabilities opened the possibilities for neural network based approaches (e.g. Chaphalkar et al., 2015) or data mining (e.g. Art Chaovalitwongse et al., 2012)

A common denominator of the decision support tools in the literature is high information demand, and increased complexity. This results in decreased transparency of the tools and a need for specialized experts. Contrary to the reported good performance of these tools, acceptance among practitioners is often low, as e.g. discussed by Hartono and Yap (2011) on the use of prescriptive models for mark-up decisions in the construction industry.

The descriptive stream on project decisions is concerned with the study of individual and group decision-making behaviour According to Stingl and Geraldi (2017), the research on behavioural decision-making can be grouped into three schools of thought: the Reductionist school that explores cognitive limitations; the Pluralist school that analyses opportunistic and political behaviour; and the Contextualist school that discusses sensemaking processes (Weick, 1995) in project decision-making.

Within the Reductionist school, the topic of cognitive biases dominates the academic discussion (e.g. Lovallo and Kahneman, 2003; Shore, 2008). This stream of literature is rooted in the concept of heuristics and biases (Tversky and Kahneman, 1974), and thus aims at identifying behavioural deviations from rational, normative decision-making, and suggesting de-biasing strategies.

However, as Stingl and Geraldi (2017) highlighted, general decision science literature also positively discusses heuristics as successful decision strategies. Their review indicated that this discussion is currently not extended to project studies.

We performed an additional literature search for this paper, identifying project literature referring to key publications on adaptive heuristics. As shown in Table 1, we identified only four recent publications in the field that build explicitly on adaptive heuristics. Further three aligned publications contribute to adaptive heuristics but do not build on it explicitly.

Four of these publications explicitly evaluated the effectiveness of the applied strategy. The remaining three publications were descriptive, discussing practitioners' use of heuristics in their decision-making. In a nutshell, the research demonstrated that adaptive heuristics are used in project decisions, that they seem to perform well when compared with regression models. However, not all heuristics are equally suitable to a specific decision problem.

Table 1 - Overview of literature on heuristics in project publications

	Explicit link to heuristics	Aim of study
Albar and Jetter, 2011	Yes	Prescriptive
Eriksson and Kadefors, 2017	Yes	Descriptive
Hartono and Yap, 2011	Yes	Descriptive
Mathews, 2010	Yes	Descriptive
Maytorena et al., 2007	No	Descriptive/ Prescriptive
Van Oorschot et al., 2011	No	Descriptive/ Prescriptive
Winch and Maytorena, 2009	No	Descriptive/ Prescriptive

Thus, while there is a slow rise in interest in adaptive heuristics as a lens to *understand* expert decision-making in projects, it is not yet systematically considered as a tool to *improve* project decision-making.

This paper will develop a holistic view on adaptive heuristics that supports prescriptive research. This shall foster the development of novel project decision tools that reconcile the need for both intuitive and analytical decision support.

3. Theoretical background - adaptive heuristics

Heuristics are simple decision strategies that deliberately omit some of the available information to make fast inferences. They are often linked with the concept of cognitive short cuts, as this type of reasoning is similar to the natural cognitive processes during fast decision-making of humans and other animals (Gigerenzer and Brighton, 2009). Yet, heuristics as a theoretical concept go beyond the idea of simplifying strategies that introduce bias and error. Still, it is particularly the latter notion that receives significant attention in both general and project decision literature, following a research stream rooted in Tversky and Kahneman’s seminal paper “Judgement under uncertainty: heuristics and biases” (1974).

The difference between the ‘heuristics and biases’ program and the ‘simple heuristics’[1] program proposed by Gigerenzer and Brighton (2009) is a philosophical one, with fundamentally different ontological and epistemological views.

The ontological gap roots in the different view on heuristics as either helpful tools or introducers of error. While both programs agree that heuristics produce – to some extent – inaccurate assessments, the simple heuristics program has systematically questioned the ‘accuracy-effort-trade-off’-paradigm. The assumption of this paradigm is that higher effort, i.e. better models and more knowledge, will inevitably lead to more accurate decisions. However, the discussion of the bias-variance-dilemma by Brighton and Gigerenzer (2015) provided examples and mathematical arguments, why and where simplistic models may – in highly complex and uncertain environments – be more accurate in prediction than sophisticated mathematical models. This systematic analysis is in line with prior findings in which simple heuristics performed well for realistic judgement problems (Gigerenzer and Gaissmaier, 2011 and references therein).

The epistemological difference of the two programs relates to the type of research that is pursued by the programs. The heuristics and bias program is foremost output-oriented and hence purely descriptive, identifying the roots and consequential biases for individual heuristics. An example is the well-studied effect of perceived self-efficacy on over-optimistic project forecasts (Sengupta et al., 2008). The adaptive heuristics program, on the other hand, assumes a process-oriented view with an additional prescriptive aim. It explores the decision process itself, what information is considered (further referred to as: cues), and in which way. It furthermore tackles the question: how good does a specific heuristic perform as decision strategy, compared to other heuristics and conventional decision models?

This research program has subsequently identified a variety of different heuristics that succeed in specific decision problems. An overview of six selected adaptive heuristics is given in

[1] The literature uses different terms for the same concept, e.g. adaptive heuristics, simple heuristics, or fast-and-frugal heuristics, etc. For simplicity, we will refer to this class as ‘adaptive heuristics’ or simply ‘heuristics’ across the remainder of the article.

Table 2.

Table 2 – Six examples of well researched adaptive heuristics (from Gigerenzer and Brighton (2009), abridged[2])

Adaptive Heuristic	Definition
Recognition heuristic	If one of two alternatives is recognized, infer that it has the higher value on the criterion.
Take-the-best	To infer which of two alternatives has the higher value, go through cues in order of validity until there is a cue that discriminates the two alternatives, then pick the alternative this cue favours.
Tallying	To estimate a criterion, do not estimate weights but simply count the number of positive cues.
Satisficing	Search through alternatives and choose the first one that exceeds your aspiration level.
Imitate the majority	Consider the majority of people in your peer group and imitate their behaviour.
Fast-and-Frugal-Trees	Skimmed down decision tree with each node connecting only to one further node and an exit.

Following the particular onto-epistemological stance, there are two cornerstone concepts in behind heuristics: ecological rationality and a basic descriptive structure of the process.

Ecological rationality is a concept that follows the argument of Simon's Scissors (1990). Simon claimed that rationality is not only bounded by the decision-maker's cognitive limitations, but is also a consequence of the task environment, e.g. the fuzziness of information, the potential to learn, or the possibility to change choices. Therefore, Gigerenzer and Brighton (2009) claim that there is not only rational and irrational behaviour, as is the key assumption of the heuristics and biases program, but also an ecologically rational behaviour. This refers to the rational choice of a heuristic as decision strategy, based on its suitability to the context of the specific decision problem.

Individual definitions of conditions in which a heuristic is ecologically rational are varying in specificity and focus (cf. Gigerenzer and Brighton, 2009). Broadly**,** the defining parameters can be separated in two groups: those oriented towards the predictive validity of specific elements of the heuristic, and those defined through a more general description of the environmental factors of the decision.

[2] Fast-and-Frugal-Trees added from Gigerenzer and Gaissmaier (2011)

The first group considers attributes of cues (validity, variance of validity, redundancy) that favour good approximations of the 'right' answer. For example, for the Recognition heuristic, the definition is "*recognition validity >.5*" (ibid p.130), i.e. the heuristic is ecologically rational if in random samplings of e.g. city names, the recognition of one of the two names has a > 50% probability of predicting the bigger city correctly.
The second group is following environmental parameters like a rapidly decreasing number of alternatives (Satisficing), or lack of learning opportunities (Imitate the Successful). The underlying assumption for these definitions is that we cannot obtain the 'right answer' but rather only 'good enough answers'.

The identified **structural elements of heuristics** are an output of the process oriented research. The described elements serve as a common framework to describe heuristics. These three elements are: first, a search rule, defining the way in which information is gathered; second, a stopping rule, defining the end of the information search; third, a decision rule, defining how the gathered information informs the decision.
Examples of this structure (taken from Artinger et al. (2015)) are, e.g. for Recognition (p. 42):

> *(1) Search for an object that you recognize.*
> *(2) Stop as soon as one object is recognized.*
> *(3) Infer that the recognized object has the higher value with respect to the criterion.*

Or alternatively for Satisficing (ibid, p. 40):

> *(1) Set an aspiration level and search through objects.*
> *(2) Stop search when the first object meets the set aspiration level.*
> *(3) Choose this object.*

Heuristics are an emerging field, and new heuristics are identified across different application domains. Hence systematic presentations organize them differently according to the intended use. However, the comprehensive typologies presented by e.g. Gigerenzer and Gaissmair (2011) or Artinger et al. (2015), follow the structure of the heuristic but not the context in which they are ecologically rational.

4. A conceptual model of project decisions

As discussed in the literature review, heuristics have received scant attention from project scholars. The key limitation of current research is the focus on descriptive models and limited attention to prescriptive results, which can provide useful alternatives to current decision practices.

The key for such prescriptive models is the concept of ecological rationality, i.e. the link between individual heuristics and specific decision contexts in which they can succeed. We argue that available approaches fail to create a systematic, conceptual link between decision context and successful heuristics because of two reasons: First, current typologies focus on structure of the heuristic rather than a systematic grouping by conditions for ecological rationality. This clouds potential applications of the concepts to other fields. Second, current research is organized around an empirical understanding of heuristics. Given the diversity of real-world decision contexts, this spotlight-approach without systematic discussion of the context, does not inform deduction of other applications in which these heuristics may strive.

We suggest that research will benefit from a more conceptual understanding that builds on a systematic link between decision context and definitions of ecological rationality. Neither the literature on heuristics nor project studies have yet taken the bold step to connect findings into a conceptual model.

The model presented in this section contributes to closing this gap. We build on the individual definitions of ecological rationality, but organize them in a manner relevant and applicable to project decisions. Thereby, this model allows systematic and analytic linking of the decision context with suitable heuristics.

The proposed conceptual model builds on two key considerations. First, ecological rationality is defined through certain specific characteristics of the decision. Second, project decisions typically consist of several judgement and choice tasks, which can be individually supported through heuristics.
Hence, the dimensions of the conceptual model are decision characteristics (represented by type of uncertainty) and individual decision tasks (represented by judgement and choice). The next two sections explain and describe these concepts.

a. Decision context: Type of uncertainty

To characterise the decision context, we follow different definitions of ecological rationality. As stated in the discussion of the theoretical background, there are two well distinguishable groups of heuristics: the ones that seek to approximate the 'right' answer, and those that aim for the 'good enough'. These two philosophies imply two different uncertainty concepts. Comparable notions are already present in the project literature: e.g. Zhang et al.'s (2011) separation of 'risk as objective fact' vs. 'risk as a subjective construction', or Sanderson's (2012) classifications: *a priori* and statistical probability, and subjective and socialized probability.

Yet, we rely on a more abstract concept to make the philosophical differences explicit. Therefore, we build on and expand the concept of two uncertainty types proposed by Colyvan (2008, p. 646): first, "*uncertainty about some underlying fact of the matter*" (type A), and second, "*uncertainty where there is no fact of the matter*" (type B). We expand this concept insofar, as Colyvan only referred to uncertainty about a current state, but not uncertainty regarding the future.

For the purpose of this paper, uncertainty refers to the potential error of an estimation that has been made regarding the current or future value of a criterion (e.g. profit, technical performance, customer acceptance)[3]. Hence, the potential margin of error defines the uncertainty of this estimation. If the potential margin of error is low, so is the uncertainty, and vice-verse. For estimations based on mathematical models, like linear regression or heuristics, the margin of total error is described as the sum of the model variance, the model bias squared, and random, irreducible noise (Brighton and Gigerenzer, 2015).

$$\text{Total error} = \text{variance} + \text{bias}^2 + \text{noise}$$

The model variance is a result of the fuzziness of the individual cues used in the model and increases with the number of cues. The bias is a function of the model accuracy in terms of representing reality. Noise is a random term, specific to the decision problem.

In type A uncertainty, the influence of the random noise on the overall error of the judgement will be marginal. The potential of error, the uncertainty, results from the variance and the bias

[3] At this point, we do not discriminate between uncertainty with known probabilities (cf. 'risk' in the classical definition by Knight) and unknown probabilities.

in the model applied for the estimation. Type A uncertainty is at the centre of most traditional approaches dealing with uncertainty. The underlying assumption is the existence of a knowable and objective truth, either as deterministic or stochastic process with defined, narrow probabilities (as opposed to ‘flat tails’). We therefore refer to this type as ‘knowable uncertainty’, which results from missing knowledge and information. This uncertainty may be reduced or even eliminated by gathering further insight.

Moreover, for Type A, uncertainty will naturally decrease as the moment of materialisation approaches. For example, the estimations of when a certain supplier will deliver a critical part, or what the performance of a newly designed system will be, will increase in accuracy over time. While it may not be economically sensible to gather full knowledge, knowable uncertainty builds on the notion that full knowledge is, in principle, achievable.

In contrast, type B uncertainty cannot be eliminated through further gathering of knowledge. We therefore refer to is as ‘unknowable uncertainty’. In Colyvan’s discussion, this type of uncertainty results from linguistic vagueness, e.g. context depending, subjective interpretation of terms. This applies particularly to the issue of project success (Kreiner, 2014), which is driven by different and evolving stakeholder perceptions. We expand Colyvan’s type B by including unknowable future developments. This expansion introduces ‘unpredictability’ as either the consequence of randomness that follows an unknown or very broad probability distribution (‘fat tails’), or as ‘practical’ unpredictability, e.g. due to the complexity of a system, high pace of change, or an infeasible amount of data collection or modelling effort.

This type of unknowable uncertainty is relevant to projects, as projects shape the future while they proceed, following new insights and changes in the environment (Kreiner, 1995; Pitsis et al., 2003). In any of these cases, it is the random, unknowable ‘noise’ that dominates the error, i.e. the uncertainty. Therefore, additional knowledge and attempts to improve the decision support model will not significantly reduce the uncertainty. Typical examples for this type of uncertainty are ‘black swans’, events with very low probability but high impact, like catastrophic weather events, the sudden absence of a key project member, or a critical incident at a production facility. Furthermore, this type of uncertainty affects any search for the ‘best’ alternative, be it technology, location, or staffing, where what is ‘best’, is a result of developments within the project.

Typically, a mixture of both knowable and unknowable uncertainty affect project decisions. For example, the decision of whether to accelerate project completion may need consideration of: when would we finish without acceleration (Type A uncertainty in normal condition, Type B regarding rare events)? How effective will the acceleration action be (foremost Type A)? How will the customer react to a delay: is it even valuable to accelerate (Type B)?

The differences are illustrated in the figures below. While Type A uncertainty decreases as the project progresses and more information is known about the project, Type B uncertainty is unknowable: it comes as a surprise and/or we cannot reduce the uncertainty by gathering more information.

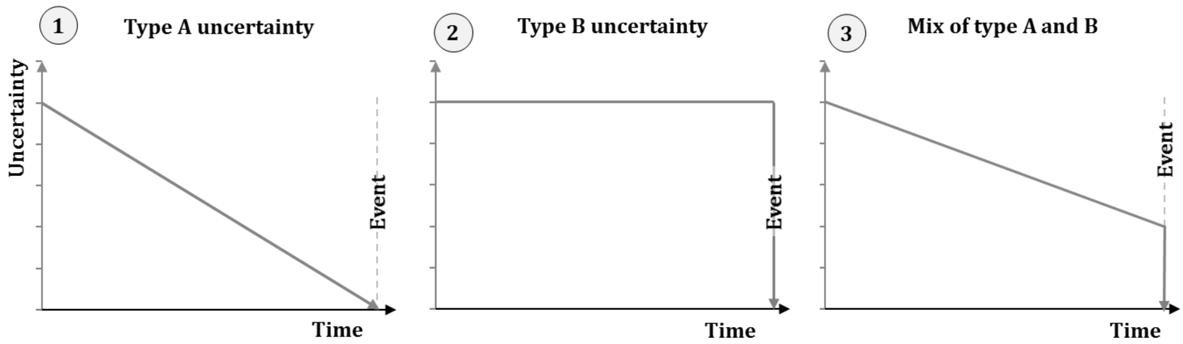

Figure 1 - Types of uncertainty: (1) knowable uncertainty, decreasing over time; (2) unknowable uncertainty, only resolved as event takes place; (3) uncertainty profile of typical project decisions.

Coming back to the relevance of the noise term for uncertainty, this notion allows grouping of heuristics according to the environments in which they perform best. On the one hand are those heuristics that define their ecological rationality through the validity of individual or several cues and the cue environment. Hence, they evaluate the contribution of the cues to correct inferences (cf. "*Recognition validity >0.5*"). The aim is to reduce the total error, and to make fast-and-frugal inferences about a situation where information is limited. These heuristics build on the assumption of a knowable, correct decision, which is challenged by a lack of knowledge. Hence, they are connected with knowable uncertainty: the better the inferences of a decision strategy based on a limited set of cues, the better it is suited for the context.

On the other hand are those heuristics for which the definition of ecological rationality follows a more general description of the decision environment. Those heuristics do in consequence not strive for one correct inference but a good-enough choice or judgement. This approach connects to managerial strategies suited to cope with unknowable uncertainty, e.g. robust (Perrow, 1999) or resilient strategies (Pich et al., 2002; Weick and Sutcliffe, 2007), or even approaches in line with Taleb's (2012) controversial notion of anti-fragility.

Following the definitions of ecological rationality for different heuristics proposed in the literature, Table 3 groups selected heuristics into the two proposed categories of uncertainty.

Table 3 - Definitions of ecological rationality (adapted from Gigerenzer and Brighton, 2009) linked with types of uncertainty

Heuristic	Ecologically rational when	Type of uncertainty
Recognition heuristic	Recognition validity >0.5	Type A
Take-the-best	Specific cue environments (see Gigerenzer and Brighton, 2009) that analytically have shown to achieve good fits to observations.	Type A
Tallying	Cue validities vary little with low redundancy.	Type A
Satisficing	Number of alternatives decreases rapidly.	Type B
Imitate the majority	Stable or slowly changing environment with costly or time-consuming information search.	Type B
Fast-and-Frugal-Trees	Specific cue environments (see Gigerenzer and Gaissmaier, 2011) that analytically have shown to achieve good fits to observations.	Type A

b. Decision task

Various theoretical and descriptive models sketch decision-making. They disagree in their view on how individual decision tasks are made, how explicit these tasks are, whether all of them occur in all decisions, or whether they follow a particular order. Some descriptive studies have highlighted the 'messiness' of group decision-making (e.g. Lindblom's 'muddling through' (1959) or the 'garbage can model' by Cohen et al. (1972)). Yet, there is a wide consensus in behavioural decision-making that decisions involve individual decision tasks. Thus, decision tasks represent a common denominator across the literature.

We therefore argue that a model including separable decision tasks – independent of whether they occur sequentially, in parallel, or interactively – is suited for the proposed research for two reasons. First, it is in line with the theoretical assumptions of heuristics which adopt a process-oriented view on cognition and reasoning. Second, a task view helps practitioners connect intuitively what kind of heuristics to use according to the kind of decision tasks they are currently undertaking. Hence, decision tasks are convenient for the development of prescriptive conceptual models on project decisions as it connects with the ‘making’ of the decision.

The type of the decision task is moreover relevant because it delimitates the core question of what the decision is about. Through understanding the core question, it is easier to match generic project decision problems with existing research on heuristics.
Available theoretical models provide a finely-granulated view on individual decision tasks, usually including at least the elements: problem identification/framing, alternative identification, alternative comparison, alternative selection, and implementation. Yet, these tasks can be grouped in two distinguishable categories (Einhorn and Hogarth, 1981): judgement and choice.

Judgment is concerned with the assessment of a current or future situation. This assessment may regard a state of things, e.g. whether the project is still on track, or causal relations in the socio-technical systems, e.g. the customer reaction to a claim. It does not imply a specific action or choice but rather informs the decision by providing an answer to the questions: Where are we? Where are we heading? What do we want? Or: how did we end up here? For example, when choosing a key supplier, we will judge project needs, whether and why the specific delivery is critical, the extend of our knowledge about our needs, potential suppliers in the market, our past relationships, etc.

Choice, on the other hand, builds on factual information and/or judgements to select a particular course of action. It answers therefore the question of: How do we get to where we want to go? Going back to the example above, choice would be the actual decision for a specific supplier, based on our judgment of the situation.

Project decisions usually contain several judgement and choice tasks in parallel or sequential. We argue that separating these and providing the right support for either – more than a holistic support tool for the entire decision – can contribute to increased efficiency and efficacy of the decision process. Moreover, heuristics can be easily grouped in those successfully supporting judgement tasks or choice tasks.

To link the type of decision task – choice or judgement – with a specific heuristic, we rely on literature definitions of the structural elements, specifically the decision rule. These rules refer either to the estimation of a criterion value (judgement), or to a choice of action. Table 4 groups selected heuristics into the two proposed categories of uncertainty.

Table 4 - Structural definitions of heuristics (cited from Artinger et al., 2015)[4]. SeR: search rule, StR: stopping rule, DR: decision rule.

Heuristic	Structural definition	Decision Task
Recognition heuristic	SeR: Search for an object that you recognize. StR: Stop as soon as the object is recognized. DR: Infer that the recognized object has the higher value with respect to the criterion	Judgement
Take-the-best	SeR: Order cues by their validity. StR: Stop on finding the first cue that discriminates between the alternatives. DR: Choose the alternative with the higher cue value.	Choice
Tallying	SeR: Search through cues in any order, add positive cues to the tally, and deduct negative cues from it. StR: Stop after *n* cues DR: Decide for the alternative with the higher tally. If there is *[..]* a draw, guess.	Choice
Satisficing	SeR: Set an aspiration level and search through objects. StR: Stop search when the first object meets the set aspiration level. DR: Choose this object.	Choice
Imitate-the-majority	SeR: Search through behaviour of individuals in your peer group. StR: Stop search when you have identified the behaviour of the majority. DR: Imitate this behaviour.	Choice
Fast-and-Frugal Tree	SeR: Search through cues in a predetermined order. StR: Stop search as soon as a cue leads to an exit. DR: Classify the object accordingly.	Judgement

5. Uncertainty type and decision task combined

Combining the two dimensions of uncertainty type and decision task, we obtain the conceptual model presented in Table 5. This model serves to address project decisions in a systematic way and is suitable to establish a systematic link to heuristics.

[4] Except: Imitate-the-majority (following Gigerenzer and Brighton (2009)) and Fast-and-Frugal Trees (cited from Gigerenzer and Gaissmaier (2011))

Table 5 - Conceptual model of project decision and heuristics, organized by uncertainty type and decision task. Definitions for the assignment of the heuristics in the model can be found in (1) Gigerenzer and Brighton (2009), (2) Artinger et al. (2015) and (3) Gigerenzer and Gaissmaier (2011).

	Type A (knowable) uncertainty	**Type B (unknowable) uncertainty**
Judgement	**Decision problem**: estimations based on limited knowledge about situation or causalities **Applicable heuristics, e.g.**: - Fast-and-Frugal-Tree (3) - Recognition (1) - Fluency (1) - Similarity (2) 1	**Decision problem**: estimations based on ambiguous meaning or unpredictable events **Applicable heuristics**: None (see main text) 2
Choice	**Decision problem:** Choice based on criteria for which there is limited knowledge **Applicable heuristics, e.g.:** - Take-the-best (1) - Tallying (1) 3	**Decision problem:** Choice based on criteria for which it is impossible to gain *a priori* knowledge. **Applicable heuristics e.g.:** - Satisficing (1) - 1/N (equality heuristic) (1) - Imitate the majority / the successful (1) Tit-for-Tat (1) 4

We argue that there are no suitable heuristics for judgements under unknowable (Type B) uncertainty (quadrant 2). This follows logically, as an accurate judgement is, by definition, not possible in this type of uncertainty. As the irreducible random noise defines the error of any judgement, predictive capabilities of any analytical approach will be low.

This notion is crucial for the choice of strategies to manage uncertainty. In quadrant 2, there are two possible approaches: reduce the roots of unknowable uncertainty (e.g. clarify ambiguous or vague views of different stakeholders), or prepare for the unknown or unexpected through robust, resilient or anti-fragile strategies.

Based on this model we make three propositions:

First, the discussion of the two different types of probability highlights the necessity to review the notion of ‘predictive capability’. The core body of heuristic literature frames predictive capability following a factual, measurable *a priori* or *a posteriori* criterion. We claim that this is only suitable for Type A uncertainty. Following the argument in the two previous paragraphs, Type B uncertainty only affect choices, more specifically the search for a ‘good enough’ choice. Therefore, we suggest that heuristics in the fourth quadrant of the model warrant an alternative assessment of predictive capability reflecting these restrictions. Hence our proposition:

P1: An *a posteriori* qualitative assessment of the overall decision outcome, potentially informed by subjective judgement, is better suited to study predictive capability of heuristics for choice under unknowable uncertainty, than a specific quantitative criterion.

Second, as descriptive studies have revealed, practitioners use heuristics intuitively. Yet, we suggest that there is a difference in the effectiveness of this intuition for the two dimensions of the presented model. We argue that this difference results from the level of abstraction needed to make the correct selection. Decision tasks link in a non-abstract, direct way to decision-making practice, thus allow simple, intuitive selection. However, assessment of uncertainty – thus the selection of the ecologically rational heuristic – requires a higher level of abstraction of the decision context, which may not happen intuitively. Hence follows:
P2: Practitioners are intuitively more effective in selecting a heuristic based on decision task than based on uncertainty type.

Yet, expert heuristics are the result of learning and feedback (Rieskamp and Otto, 2011). Hence we suggest that both experience and education may increase the ability of practitioners to apply heuristics ecologically rational. Therefore we propose:

P3a: Clear and timely feedback on decisions will increase the effectiveness of practitioners to select appropriate heuristics according to uncertainty type.

P3b: Education of practitioners, enabling to reflect on the decision context, will increase the effectiveness of practitioners to select according to uncertainty type.

When placing the scant research on heuristics in projects within the proposed model, we obtain an insight on its applicability and the validity of the propositions made before. We will demonstrate this with three examples:

First, Mathews (2010) describes the use of fast-and-frugal trees for innovation project screening in a company case. Fast-and-frugal trees are, according to the model, suitable for judgement tasks under knowable (Type A) uncertainty. The presented case screened opportunities for alignment with the portfolio strategy, so the application for a judgement task ('fits the strategy') is in line with the model. Yet, as the study was purely descriptive, Mathews did not test the accuracy of the judgement. He thus does not provide insight on whether the heuristic fits the type of (dominating) uncertainty. A quantitative, performance oriented comparison with e.g. Tallying or Satisficing as choice, rather than judgement strategy, would constitute a worthwhile follow-up investigation.

Second, Albar and Jetter (2011) similarly discuss the use of Take-the-Best and Tallying as a portfolio selection strategy at the front end. Other than Mathews, their focus is on the capability of the strategies to choose successful projects and reject unsuccessful ones, based on fuzzy information of 52 project simulations. As the simulations were based on pre-determined influencing factors of the individual cues, the uncertainty within the sample pertained to Type A (only minor randomness in sample generation). The practical problem was thus choice under knowable uncertainty, and the selected two heuristics in line with the model propositions for this problem. Albar and Jetter found, that Tallying performed equally well as the best linear regression model used for comparison in the study. Take-the-Best outperformed all other models for selection of successful projects, yet showed low performance for rejecting unsuccessful projects.

Third are two connected studies by Maytorena and Winch (Maytorena et al., 2007; Winch and Maytorena, 2009). These studies explored the cognitive processes of experts during risk identification in the front end phase of construction projects. Their research builds on the method of active information search coupled with cognitive mapping, and did not explicitly link to heuristics. Yet, they discovered that information search strategies that build on a series of connected cues, similar to fast-and-frugal trees (although not explicitly identified as such), performed better in identifying risks than a sequence of single cue strategies. This is in line with what the conceptual model would suggest for the described task: judgement ('is a risk/is not a risk') under knowable uncertainty (as the case was designed by the researchers, based on 'known' risk profiles).

6. Discussion

In this paper, we presented a systematic, common organization of project decisions and adaptive heuristics. We identified the need for such a new conceptual model to foster prescriptive research on heuristics in projects, as prior typologies did not systematically connect to the context of project decisions. To create a suitable presentation, we built on two dimensions: decision task (judgement, choice) and type of uncertainty (knowable, unknowable). Particularly we pointed to the importance of 'unknowable uncertainty', rooted in ambiguous success definitions, and unpredictability as projects shape the future as they proceed.

Thereby, we contribute to project studies, practice and research on adaptive heuristics. For project studies, we presented a new theoretical concept to understand and improve expert decision-making, which has not yet received particular attention in the literature. Moreover, we provided a framework that is informative for descriptive and prescriptive research on decision-making in project, with applicability beyond adaptive heuristics. Finally, the presented model allows moving from the current dominating descriptive approach in the scant project literature on adaptive heuristics, to a prescriptive approach.

For practice, we conclude that such a strengthened prescriptive research will contribute to the development of new robust and easy to apply decision tools.

For the studies on adaptive heuristics, we contributed twofold. First, we proposed a new mode for organizing heuristics. This new approach is at a higher level of abstraction than previously presented typologies. It hence enables a discussion of the underlying theories beyond the contextual application. Second, we highlighted the boundaries of current discussions on ecological rationality and predictive capability regarding their focus on knowable uncertainty. This philosophical gap has previously not been explicitly addressed in the literature. It hence merits consideration and development of new measures for predictive capability.

Yet, the proposed model is limited in three ways:

First, uncertainty types are only one way to describe the decision context and organize the various individual definitions of ecological rationality. While we argue that it is a helpful concept, we acknowledge that there may be other suitable approaches. Especially with regards to heuristics that strive under knowable uncertainty, we suggest that a typology that considers individual roots of uncertainty – e.g. cue fuzziness, variability or variance of cue validity, etc. – may better inform the prescriptive research. Yet, such an organization would not support heuristics that strive in unknowable uncertainty, thus is limited in itself.

Second, there is a debate within the adaptive heuristics research community, whether the structural description of the 'three rules' apply to all heuristics – already known or yet to be discovered. This applies particular to the concept of 'simple rules' (Bingham and Eisenhardt, 2011), which are regularly mentioned in connection with heuristics, yet typically cannot be described through the three rules. While the proposed model would, in principle, allow a model-conform classification of individual simple rules, the classification regarding 'decision task' would need to be informed by other data than literature definitions of the 'decision rule'.

Third, there is an overlap of Type A and Type B uncertainty in 'real-life' project decisions. This may cloud the judgement of which is the dominating one and hence challenge the selection of a suitable heuristic.

We believe, that while all those limitations are valid concerns with regard to the proposed model, they are less limiting than opening up new opportunities for research. We hence suggest that the proposed model in itself is valuable to identify both opportunities and limitations that can spark further research.

7. Conclusion and outlook to future research

In summary, we have introduced adaptive heuristics as a novel decision strategy to project studies. We have supplemented this introduction with a conceptual model of project decisions and heuristics, which fosters prescriptive research and thus contributes to the development of new decision support strategies for practice.

However, the proposed model is only a first, informative mode of organizing heuristics and is limited due to its simplicity. Thus we see two general opportunities for research to build on and develop the proposed conceptual model. These opportunities are first, further refinement of the model within the quadrants defined in Table 5. Second, testing the model through prescriptive research on various types of heuristics for one context, or one heuristic for various context. Such research will inform both further theorizing on adaptive heuristics and development of tools for project practice.

Over the past decades, project research moved towards the actuality of practitioners, acknowledging the diversity and complexity of project decision-making. With the presented approach we contribute to a next step towards practice, allowing the development of pragmatic, yet theoretically sound approaches that fit the day-to-day life of practitioners. We have presented an open toolbox that warrants exploration by theory and practice alike.

8. References

Al-Subhi Al-Harbi, K.M., 2001. Application of the AHP in project management. Int. J. Proj. Manag. 19, 19–27.

Albar, F.M., Jetter, A., 2011. An investigation on Fast and Frugal Model for new project screening, in: PICMET: Portland International Center for Management of Engineering and Technology, Proceedings. Portland, OR.

Artinger, F., Petersen, M., Gigerenzer, G., Weibler, J., 2015. Heuristics as adaptive decision strategies in management. J. Organ. Behav. 36, 33–52.

Bingham, C.B., Eisenhardt, K.M., 2011. Rational heuristics: the “simple rules” that strategists learn from process experience. Strateg. Manag. J. 32, 1437–1464.

Brighton, H., Gigerenzer, G., 2015. The bias bias. J. Bus. Res. 68, 1772–1784.

Chaovalitwongse, W., Wang, W., Williams, T.P., Chaovalitwongse, P., 2012. Data Mining Framework to Optimize the Bid Selection Policy for Competitively Bid Highway Construction Projects. J. Constr. Eng. Manag. 138, 277–286.

Chaphalkar, N.B., Iyer, K.C., Patil, S.K., 2015. Prediction of outcome of construction dispute claims using multilayer perceptron neural network model. Int. J. Proj. Manag. 33, 1827–1835.

Cohen, M.D., March, J.G., Olsen, J.P., 1972. A garbage can of organizational choice. Adm.

Sci. Q.

Colyvan, M., 2008. Is probability the only coherent approach to uncertainty? Risk Anal. 28, 645–652.

Einhorn, H.J., Hogarth, R.M., 1981. Behavioral Decision Theory: Processed of Judgment and Choice. Annu. Rev. Psychol. 32, 53–88.

Eriksson, T., Kadefors, A., 2017. Organisational design and development in a large rail tunnel project - Influence of heuristics and mantras. Int. J. Proj. Manag. in press.

Gigerenzer, G., Brighton, H., 2009. Homo Heuristicus: Why biased minds make better inferences. Top. Cogn. Sci. 1, 107–143.

Gigerenzer, G., Gaissmaier, W., 2011. Heuristic decision making. Annu. Rev. Psychol. 62, 451–482.

Gigerenzer, G., Hertwig, R., Pachur, T., 2011. Heuristics: The foundations of adaptive behavior, Heuristics: The foundations of adaptive behavior. Oxford University Press, New York.

Hartono, B., Yap, C.M., 2011. Understanding risky bidding: A prospect-contingent perspective. Constr. Manag. Econ. 29, 579–593.

Huang, C.-C., Chu, P.-Y., Chiang, Y.-H., 2008. A fuzzy AHP application in government-sponsored R&D project selection. Omega 36.

Kreiner, K., 2014. Restoring project success as phenomenon, in: Lundin, R.A., Hällgren, M. (Eds.), Advancing Research on Projects and Temporary Organizations. Copenhagen Business School Press, Copenhagen.

Kreiner, K., 1995. In search of relevance: Project management in drifting environments. Scand. J. Manag. 11, 335–346.

Leybourne, S., Sadler-Smith, E., 2006. The role of intuition and improvisation in project management. Int. J. Proj. Manag. 24, 483–492.

Lindblom, C.E., 1959. The science of “Muddling Through.” Public Adm. Rev. 19, 79–88.

Lovallo, D., Kahneman, D., 2003. Delusions of success: How optimism undermines executives’ decisions. Harv. Bus. Rev. 81, 56–63.

Mathews, S., 2010. Innovation portfolio architecture. Res. Technol. Manag. 53, 30–40.

Maytorena, E., Winch, G., Freeman, J., Kiely, T., 2007. The influence of experience and information search styles on project risk identification performance. IEEE Trans. Eng. Manag. 54, 315–326.

McCray, G.E., Purvis, R.L., McCray, C.G., 2002. Project management under uncertainty: The impact of heuristics and biases.pdf. Proj. Manag. J. 33, 49–57.

Miller, R.W., 1962. How to plan and control with PERT. Harv. Bus. Rev. 40, 93–104.

Patterson, J.H., 1984. A comparison of exact approaches for solving the multiple constrained resource, project scheduling problem. Manage. Sci. 30, 854–867.

Perrow, C., 1999. Normal accidents: living with high-risk technologies. Princeton University Press, Princeton, NJ.

Pich, M.T., Loch, C.H., Meyer, A. De, 2002. On uncertainty, ambiguity, and complexity in project management. Manage. Sci. 48, 1008–1023.

Pitsis, T.S., Clegg, S.R., Marosszeky, M., Rura-Polley, T., 2003. Constructing the olympic dream: A future perfect strategy of project management. Organ. Sci. 14, 574–590.

Pound, W.H., 1964. Research project selection: Testing a model in the field. IEEE Trans. Eng. Manag. EM-11, 16–22.

Rieskamp, J., Otto, P.E., 2011. SSL: A Theory of How People Learn to Select Strategies, in: Gigerenzer, G., Hertwig, R., Pachur, T. (Eds.), Heuristics: The Foundations of Adaptive Behavior. Oxford Univeristy Press, New York.

Rolstadås, A., Pinto, J.K., Falster, P., Venkataraman, R., 2014. Decision making in project management, NTNU Engin. ed. Fagbokforlaget Vigmostad & Bjørke AS, Bergen, Norway.

Sanderson, J., 2012. Risk, uncertainty and governance in megaprojects: A critical discussion of alternative explanations. Int. J. Proj. Manag. 30, 432–443.

Sengupta, K., Abdel-Hamid, T.K., Van Wassenhove, L.N., 2008. The experience trap. Harv. Bus. Rev. 86, 94.

Shore, B., 2008. Systematic biases and culture in project failures. Proj. Manag. J. 39, 5–16.

Simon, H.A., 1990. Invariants of human behavior. Annu. Rev. Psychol. 41, 1–19.

Stingl, V., Geraldi, J., 2017. Errors, lies and misunderstandings: Systematic review on behavioural decision making in projects. Int. J. Proj. Manag. 35, 121–135.

Taleb, N.N., 2012. Antifragile: Things that gain from disorder. Random House, New York.

Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: heuristics and biases. Science (80-.). 185, 1124–1131.

Van Oorschot, K.E.., Langerak, F.., Sengupta, K.., 2011. Escalation, De-escalation, or reformulation: Effective interventions in delayed NPD projects. J. Prod. Innov. Manag. 28, 848–867.

Weick, K.E., 1995. Sensemaking in organizations. SAGE Publications, Thousand Oaks.

Weick, K.E., Sutcliffe, K.M., 2007. Managing the unexpected: Resilient performance in an age of uncertainty. John Wiley & Sons.

Winch, G.M., Maytorena, E., 2009. Making good sense: Assessing the quality of risky decision-making. Organ. Stud. 30, 181–203.

Zahra, S.A., Newey, L.R., 2009. Maximizing the impact of organization science: Theory-building at the intersection of disciplines and/or fields. J. Manag. Stud. 46, 1059–1075.

Zeng, J., An, M., Smith, N.J., 2007. Application of a fuzzy based decision making methodology to construction project risk assessment. Int. J. Proj. Manag. 25, 589–600.

Zhang, H., Herazo, B., Lizarralde, G., Paquin, R., 2011. Two schools of risk analysis : A review of past research on project risk. Proj. Manag. J. 42, 5–18.